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SMART HYDROPONIC NUTRIENT MONITORING AND CONTROL SYSTEM USING FUZZY LOGIC AND IOT

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ABSTRACT

Hydroponic farming offers an efficient and sustainable solution for modern agriculture, although maintaining stable nutrient levels remains a key challenge. Previous systems often exhibited high overshoot and were unable to adapt to external changes or disturbances, and no existing research has adaptively regulated nutrient levels based on the plant's growth stage. Therefore, this study aims to develop a smart nutrient monitoring and control system for hydroponics using a Sugeno-type fuzzy logic controller integrated with an IoT-based application. Unlike prior systems that rely on fixed setpoints or only address nutrient deficiency, this system dynamically adjusts nutrient and water levels based on real time sensor data and plant growth phase. The system utilizes nutrient, water level, and temperature sensors connected to an ESP32 microcontroller, with fuzzy logic determining solenoid valve activation duration. The control system achieved stable regulation with zero overshoot, a settling time of 840 seconds, and effective recovery from nutrient disturbances. Growth tests on celery showed a 102.6% improvement in height, 275% in stem diameter, and 112.5% in leaf width compared to manual control. IoT monitoring via a mobile application ensured real time visibility of hydroponic parameters. These results demonstrate the system's capability to maintain optimal nutrient levels, improve control precision, and enhance plant productivity.

Keywords: *fuzzy logic, hydroponics, IoT, monitoring and control, nutrient level.*

I. INTRODUCTION

AGRICULTURE is a fundamental pillar of human life, providing food, livestock feed, and bioenergy. In recent decades, the agricultural sector has undergone significant transformations due to population growth, climate change, urbanization, and land degradation. The challenge of meeting increasing food demand and ensuring food security has become a global priority [1]. Hydroponic farming is emerging as an innovative solution to these challenges. This method replaces soil with a water-based nutrient solution, allowing for efficient water use and enabling farming in areas with limited or poor-quality soil [2]. Compared to conventional farming, hydroponic systems offer multiple advantages, including independence from soil conditions, increased crop yield through vertical farming (verticulture), and year-round cultivation regardless of seasonal changes [3]. In addition, hydroponic plant rearing is more profitable because it does not depend on certain seasons, allowing planting throughout the year.

A key challenge in hydroponic farming is the precise and adaptive regulation of nutrient levels. Nutrient imbalances, whether deficiency or excess, can negatively impact plant growth, quality, and productivity [4]–[8]. Currently, many farmers rely on manual nutrient control methods, which involve gradually adding nutrients and measuring concentration levels. This approach is inefficient as it lacks precision, is prone to human error, and cannot adjust dynamically and in real time to environmental fluctuations such as temperature, humidity, and light intensity.

Researchers have developed nutrient control systems for hydroponics using microcontrollers [9]–[13]. The nutrient sensors are connected to the microcontroller to monitor the data in real time. The system can activate pumps or valves to add water or nutrient solution based on preset thresholds. Although more automated and accurate than manual control, this approach is still limited to simple control logic or threshold-based control.

To improve system performance, other researchers have developed fuzzy logic-based nutrient control systems in which the system makes decisions based on linguistic rules [14]–[20]. In these studies, nutrient levels are regulated to meet a predetermined set point by activating actuators such as water pumps and nutrient pumps. Some of these researchers also include features to monitor pH, nutrient levels, and temperature in hydroponic systems, and to adjust the desired pH and nutrient levels according to the specific plant being grown using IoT [16]–[20]. Although these systems can automatically regulate nutrient levels based on sensor input and send control signals to the nutrient pump, they can only respond to nutrient deficiency and cannot correct excess nutrients in the hydroponic system.

To address this limitation, researchers have developed fuzzy logic nutrient control systems that can handle both nutrient deficiencies and nutrient excesses [21]–[26]. Using predefined rules, the system can control nutrient levels by regulating the amount of nutrients and water mixed in the reservoir, so that the nutrient levels in the reservoir are neither lower nor higher than the predefined values. The system has also been tested for control response and trialed on plants for several days. The plants grown in the nutrient-controlled hydroponic system showed better development compared to plants grown under manual control. However, the control system test results showed that the response was still not optimal due to high overshoot and the system's limited ability to quickly adapt to external changes or disturbances. In addition, no existing research can adaptively regulate nutrient levels based on plant growth stages. Sangeetha [27] states that nutrient consumption changes across stages such as germination, vegetative, reproductive, and harvest. Therefore, there is a need for a stronger focus on accurately automating nutrient distribution according to plant growth stage.

The novelty of this study lies in the development of a Sugeno-type fuzzy logic control system that dynamically regulates nutrient levels based on the plant's growth stage and is capable of correcting both nutrient deficiency and nutrient excess, an aspect often overlooked in previous studies, which typically use fixed setpoints or address only deficiencies. The control system is integrated with a smartphone application that allows users to enter plant age and monitor sensor data in real time, enabling adaptive and automatic nutrient management. The objective of this study is to improve control performance by minimizing overshoot and ensuring more accurate nutrient delivery, thereby supporting healthier plant growth compared to manual control methods. The first contribution is the development of a smart hydroponic nutrient control system using a fuzzy method that adaptively regulates nutrient levels based on plant growth stages, addressing both deficiency and excess conditions. The second contribution is the integration of real time sensor data with a smartphone interface and IoT monitoring, which minimizes overshoot and improves system responsiveness to environmental change.

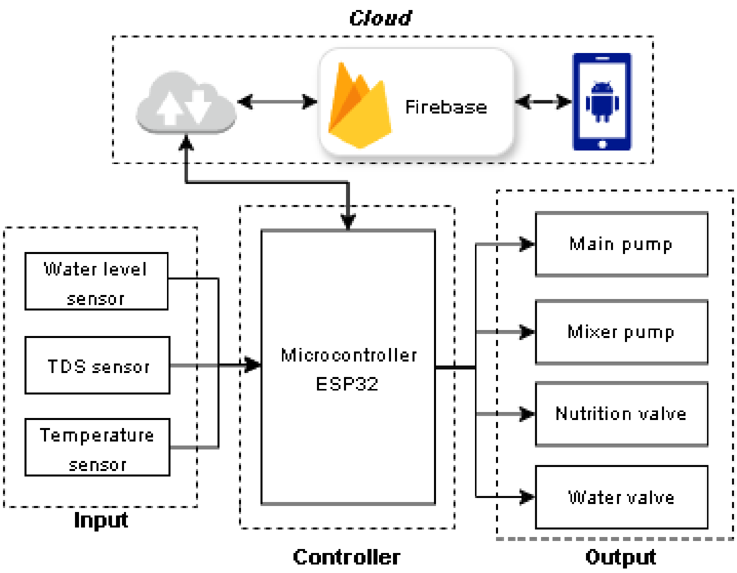


Figure 1. Nutrient Level Controller System Block Diagram

II. RESEARCH METHOD

A. System Design

1) Hydroponic System Design

The hydroponic system used in this study is the Nutrient Film Technique (NFT), selected for its continuous water circulation, which facilitates precise nutrient control. Rockwool was chosen as the planting medium because it provides excellent aeration, supporting root growth and oxygen availability.

2) Nutrient Monitoring and Control System Design

The nutrient-level controller system consists of four main blocks: input, controller, output, and cloud, as shown in Figure 1, which provides a structural overview of the system's components and their interactions. The input block includes three sensors, a TDS nutrient sensor, an HC-SR04 water level sensor, and a DS18B20 temperature sensor, which provide real time data to the microcontroller. The controller block consists of the ESP32 microcontroller, which serves as the system's core, processing sensor inputs and implementing fuzzy logic control for nutrient management. The output block comprises a main pump, a mixing pump, a nutrient valve, and a water valve, which regulates the nutrient solution in the hydroponic system. The cloud block facilitates data storage in Firebase and communication between the controller and a smartphone application through an internet connection. Similar to other studies, IoT is also used for monitoring and storing data required by the system [28], [29].

3) Fuzzy Logic Control Design

Fuzzy logic is used to control nutrient levels in the hydroponic system. Fuzzy logic offers key advantages over PID, decision trees, and machine learning in controlling hydroponic nutrient systems. Unlike PID, it does not require precise mathematical models and can handle nonlinear, uncertain conditions using simple linguistic rules. Compared to decision trees, fuzzy logic allows gradual transitions and overlapping input ranges. Unlike machine learning, it is lightweight, does not require large datasets, and is suitable for real time control on microcontrollers. These features make it effective for adaptive nutrient regulation in dynamic environments. The block diagram of the fuzzy logic control system can be seen in Figure 2. The nutrient regulation system in this study is designed as a closed loop control system, where the system continuously monitors and adjusts nutrient levels in the hydroponic bed based on real time sensor feedback.

Inputs to the control system are nutrient concentrations measured in parts per million (ppm) and water levels measured in centimeters. These values are obtained from sensors placed in the hydroponic bed. The setpoint is the nutrient concentration target that is determined based on the plant growth stage, which is set through an application. The system calculates two errors, the nutrient level error and the water level error. These errors are sent to the Fuzzy Logic Controller (FLC), which processes them using a set of predefined fuzzy rules. The controller evaluates the severity of each error and determines the appropriate control action. The controller's output consists of nutrient valve activation duration and water valve activation duration. After actuation, the sensor reads the new nutrient and water levels, providing updated input for the next control cycle. This creates a feedback loop where the system constantly self corrects to maintain optimal nutrient conditions.

In this study, a Sugeno-type FLC was chosen because it produces precise numerical outputs that match the system's needs, such as the required duration for activating nutrient and water valves. This allows accurate and adaptive nutrient and water delivery based on real time sensor readings and plant growth stages. The design of the FLC consists of three stages. First is fuzzification, which establishes membership functions for nutrient errors and water level errors. Second is inference, which develops

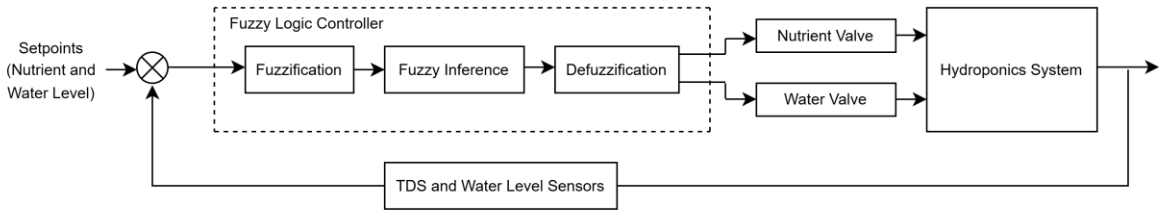


Figure 2. Fuzzy Logic Control Diagram for Nutrient Level

TABLE 1
NUTRIENT NEEDS OF CELERY PLANTS

Plant Age	Nutrition Needs
0-25 Days After Seeding	<500 ppm
1-15 Days After Planting	800 ppm
16-45 Days After Planting	800 ppm to 1700 ppm

TABLE 2
NUTRIENT LEVEL ERROR MEMBERSHIP FUNCTION

Function	Shape	Domain
Low	Linear	-500 to -75
Adequate	Trapezoid	-300 to 300
High	Linear	75 to 500

TABLE 3
WATER LEVEL ERROR MEMBERSHIP FUNCTION

Function	Shape	Domain
Very Low	Linear	-20 to -10
Slightly Low	Linear	-14 to -2

TABLE 4
NUTRIENT AND WATER OUTPUT MEMBERSHIP FUNCTION

Function	Shape	Domain
On	Single Tone	100
Off	Single Tone	0

TABLE 5
INFERENCE RULE FOR NUTRIENT LEVEL CONTROLLER

Crips input		Crips output	
Nutrition level error	Water level error	Nutrition	Water
Low	Very Low	On	On
Low	Slightly Low	On	Off
Adequate	Very Low	Off	On
Adequate	Slightly Low	Off	Off
High	Very Low	Off	On
High	Slightly Low	Off	On

rule-based decision-making using IF-THEN logic. Third is defuzzification, which converts inference outputs into crisp values for actuator control (nutrient valve and water valve).

The nutrient level error input is determined by the difference between the actual nutrient value and the desired nutrient level according to the growth stage of the plant. Table 1 [30] presents the nutritional requirements of celery plants, which vary by stage or age of the plant. The water level error is defined as the difference between the actual water level value and the desired water level setpoint. The membership functions for nutrient level and water level errors are presented in Tables 2 and 3. The fuzzy sets for nutrient level error were defined as Low (–500 to –75 ppm), Adequate (–300 to 300 ppm), and High (75 to 500 ppm), representing deficient, optimal, and excessive nutrient conditions, respectively. In Table 2, a linear function was chosen for "Low" and "High" categories, and a trapezoidal function for "Adequate" to ensure smooth transitions between deficiency, sufficiency, and excess nutrient levels. This configuration reflects the gradual change in nutrient sufficiency around the target value and allows more precise control decisions within a tolerant range. Fuzzy membership functions were applied over two overlapping ranges, Very Low (–20 to –10 cm) and Slightly Low (–14 to –2 cm), representing different degrees of water deficiency in the hydroponic reservoir. These were selected to reflect the direct and predictable impact of water level changes on the system's nutrient concentration and root oxygenation. Linearity simplifies the defuzzification process and provides faster responses to deviations.

Table 4 defines the actuator control output. A single-tone function was used for outputs, with discrete values of 0 (Off) and 100 (On). This binary approach is appropriate because the valves are solenoid-based and operate in fully open or closed states, making continuous control unnecessary and impractical. The active time of the pump is determined from the defuzzification calculation results, namely the weighted average of all active rules.

Inference rules, detailed in Table 5, govern system responses. The fuzzy inference rules were designed using expert knowledge and experimental observation. They map combinations of nutrient error and water level error into control actions. For example, when both nutrient and water levels are low, both

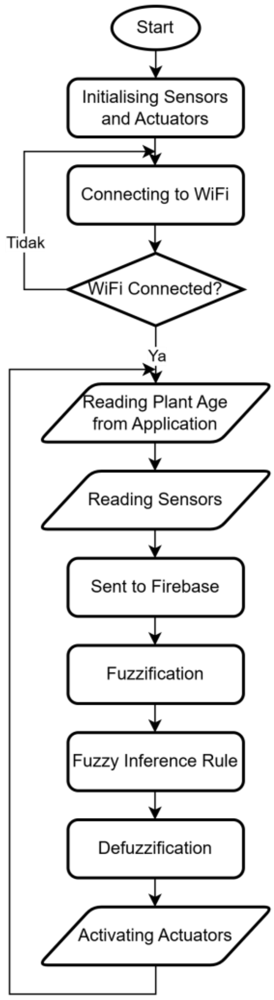


Figure 3. Flowchart of The Control System

$$WA_1 = \frac{\sum_{i=1}^{n} a_1 z_1}{\sum_{i=1}^{n} a_1} \quad (1)$$

$$WA_2 = \frac{\sum_{i=1}^{n} a_2 z_2}{\sum_{i=1}^{n} a_2} \quad (2)$$

valves are turned ON to replenish nutrients and water simultaneously. Conversely, if nutrients are excessive or adequate but the water level is low, only the water valve is activated. This rule base ensures that the system can correct environmental disturbances while maintaining nutrient balance. The defuzzification process uses the weighted average method, as shown in (1) and (2), to calculate the solenoid valve activation time based on fuzzy logic outputs. In (1) and (2), WA1 is the weighted average for nutrients, WA2 is the weighted average for water, a1 is the rule weight for nutrients, a2 is the rule weight for water, z1 is the rule output level for nutrients, and z2 is the rule output level for water.

4) System Flow Design

Figure 3 illustrates the overall system flow. The process begins by initializing the sensors and actuators, then connecting via Wi-Fi. The system reads the age of the plants from the smartphone app, then reads the sensor values to be stored in Firebase. The system checks plant age to determine nutrient needs, then processes nutrient and water level sensor data using FLC. Based on the fuzzy logic control output, the nutrient and water valves are activated according to (1) and (2). This adaptive approach ensures precise nutrient control throughout plant growth phases, accounting for variations in environmental conditions.

B. Experimental Design

The experimental design in this study aims to evaluate the performance of the fuzzy logic-based nutrient control system for hydroponic farming. Several key performance aspects are as follows.

1) Sensor Accuracy

To check the accuracy of the nutrient sensor, it was placed in 9 jars containing liquids with varying nutrient levels, and its analogue output, converted to digital by the ESP32, was compared to readings from a standardized nutrient measuring instrument. The comparison results were used to calibrate the sensor for improved accuracy. Moreover, the HC-SR04 sensor was positioned in 9 jars with different water heights, and its measurements were compared to manual readings taken with a ruler to validate accuracy.

2) Actuator Precision

The precision of the nutrient and water valves is evaluated by measuring the volume of liquid dispensed over specific time intervals. The nutrient valve was tested from 500 milliseconds to 4000 milliseconds, while the water valve was tested from 500 milliseconds to 7000 milliseconds, with the resulting volumes recorded using a measuring cup. This data is used to calibrate valve operation durations based on fuzzy output values.

3) Fuzzy Logic Response Validation

The output of the fuzzy logic system implemented in the ESP32 microcontroller is compared to the MATLAB simulation results. This step verifies the correctness and consistency of the fuzzy rule implementation.

4) IoT-Based Monitoring System Accuracy

The accuracy of the IoT-based monitoring system was tested to evaluate its ability to display real time sensor data from Firebase on a smartphone application. The accuracy is checked by comparing four sets of data, nutrient level, water level, temperature, and plant age, under different hydroponic conditions.

5) Control System Performance

To check the performance of the control system, a smart hydroponic system was applied to celery plants on the 10th day after planting, with a nutrient concentration set at 800 ppm and a water level set at 6 cm. The test was conducted for 100 minutes, with data recorded every minute. The initial nutrient level was 79 ppm. Key dynamic response metrics were measured, including overshoot and settling time.

6) System Stability and Adaptiveness

The system's ability to maintain stable operation and adjust to disturbances, such as sudden changes in nutrient concentration or water loss, was assessed. To evaluate the system's stability and adaptability, a disturbance test was conducted by manually adding water into the hydroponic reservoir and manually adding nutrient solution to the reservoir.

7) Plant Growth Metrics

The effectiveness of the control system was validated by monitoring the growth of celery plants. Plant growth testing was conducted by comparing 20 celery plants under different nutrient control methods. The first ten plants were placed in a prototype hydroponic system equipped with fuzzy logic and nutrient levels controlled by IoT, while the other ten plants were grown in a hydroponic system where nutrients were added manually. Growth observations were recorded over 10 days, measuring plant height, stem diameter, leaf width, and leaf color. Key indicators such as plant height, stem diameter, leaf width, and leaf color were compared between the fuzzy controlled and manually controlled systems.

III. Results and Discussion

A. Results

The developed hydroponic nutrient monitoring and control system is illustrated in Figures 4 and 5. This system was implemented on celery plants to regulate nutrient levels in the hydroponic growing medium. It successfully maintained optimal nutrient conditions, supporting healthy plant growth. In addition, the accompanying smartphone application using Blynk effectively displays real time data from the nutrient sensor, water level sensor, temperature sensor, and plant age, enabling users to monitor and manage the system remotely with ease.

Figure 4. Smart Hydroponic System Using Fuzzy Logic Controller Based on IoT

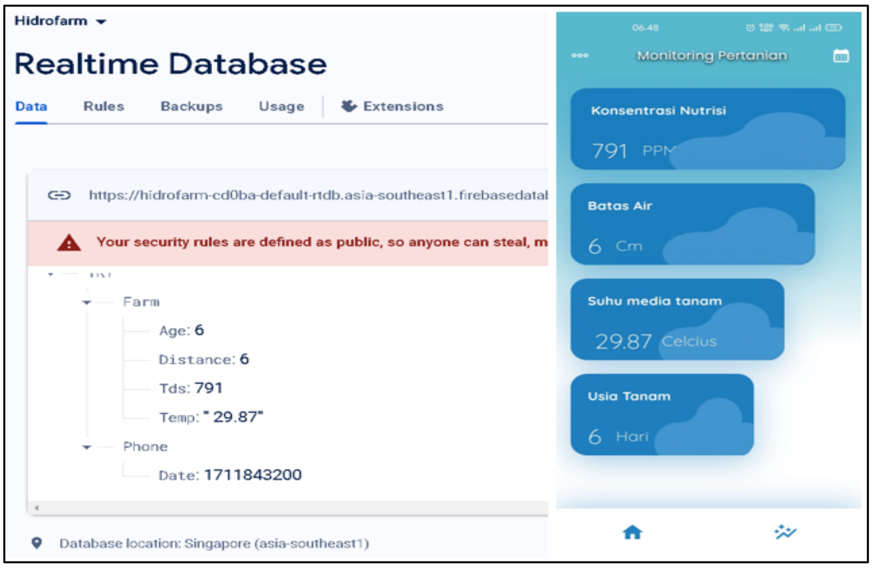


Figure 5. User Interface of Smart Hydroponic System on Smartphone

1) Sensor Accuracy

Table 6 summarizes the nutrient sensor validation results. After applying the regression equation, the average error decreased to 3.06%, which significantly improves nutrient sensor accuracy and ensures more precise nutrient dosing during system operation. In addition, as shown in Table 7, the readings from the water level sensor were identical to the actual water levels measured using a ruler. This indicates that the water level sensor provides accurate and reliable measurements, making it suitable for use in the hydroponic water level monitoring system.

2) Actuator Precision

As shown in Table 8, the nutrient valve dispenses approximately 1 ml of nutrient solution in 900 milliseconds. Similarly, Table 9 shows that the water valve releases approximately 1 ml of water in 500 milliseconds. These results indicate that both valves operate with consistent and predictable flow rates, enabling precise control over nutrient and water delivery in the hydroponic system.

3) Fuzzy Logic Validation

Table 10 presents a comparison between the fuzzy outputs generated by the ESP32 program and those obtained from MATLAB simulations, using identical input values for nutrient error and water level error. A negative nutrient error indicates that the measured nutrient level is below the desired setpoint, while a positive value indicates an excess. Water error represents the deviation of the water level from the target height in the hydroponic reservoir. The results show that the output values from both platforms are identical, confirming that the fuzzy logic system has been accurately implemented on the microcontroller. Figure 6 illustrates an example of the fuzzy logic simulation results using MATLAB.

4) IoT-Based Monitoring System Accuracy

From Table 11, it is evident that the data retrieved from Firebase remains unchanged when displayed in the smartphone application, indicating accurate and reliable data synchronisation. The application

TABLE 6
ACCURACY OF THE NUTRIENT LEVEL SENSOR

No.	The standardized nutrient measuring instrument (ppm)	TDS sensor output (ppm)	Calibrated TDS sensor output (ppm)	Error (%)
1	182	378	189	3.85
2	362	720	360	0.55
3	420	851	426	1.43
4	589	1185	593	0.68
5	657	1330	666	1.37
6	708	1450	726	2.54
7	787	1573	787	0.00
8	801	1619	810	1.12
9	1060	1779	890	16.04
		Average		3.06

TABLE 7
ACCURACY OF WATER LEVEL SENSOR (HC-SR04)

No	Actual water level (cm)	Water level measured by HC-SR04 sensor (cm)	Error (%)
1	2	2	0.00
2	3	3	0.00
3	4	4	0.00
4	5	5	0.00
5	6	6	0.00
6	7	7	0.00
7	8	8	0.00
	Average		0.00

TABLE 8
NUTRIENT VALVE PRECISION

No	Time (ms)	Nutrient Volume (ml)
1	500	0.57
2	600	0.68
3	700	0.78
4	800	0.87
5	900	0.99
6	1000	1.11
7	2000	2.23
8	3000	3.33
9	4000	4.42

TABLE 9
WATER VALVE PRECISION

No	Time (ms)	Water Volume (ml)
1	500	9.80
2	1000	19.90
3	1500	32.00
4	2000	40.00
5	2500	50.00
6	3000	60.00
7	4000	80.00
8	5000	100.00
9	6000	120.00
10	7000	140.00

TABLE 10
FUZZY LOGIC VALIDATION

Input		Output for Nutrient Valve		Output for Water Valve	
Nutrition Level Error	Water Level Error	ESP32	MATLAB	ESP32	MATLAB
-379	-17	100	100	100	100
-350	-12	100	100	50	50
-291	-14	96	96	100	100
-184	-11	51	51	25	25
-48	-9	0	0	0	0
19	-6	0	0	0	0
136	-16	0	0	100	100
223	-12	0	0	90	90
291	-10	0	0	98	98
340	-6	0	0	100	100

successfully received and displayed nutrient and water level, temperature, and plant age data transmitted from the ESP32 microcontroller via the internet. Users could observe real time changes in the hydroponic conditions, such as nutrient level adjustments or water level fluctuations, which were

TABLE 11
IOT-BASED MONITORING SYSTEM ACCURACY

Firebase				Smartphone Application			
Nutrient Level (ppm)	Water Level (cm)	Water Temperature (°C)	Plant Age	Nutrient Level (ppm)	Water Level (cm)	Water Temperature (°C)	Plant Age
300	15	28	6	300	15	28	6
324	10	28	6	324	10	28	6
566	8	28	6	566	8	28	6
857	5	27	6	857	5	27	6
1145	13	27	6	1145	13	27	6

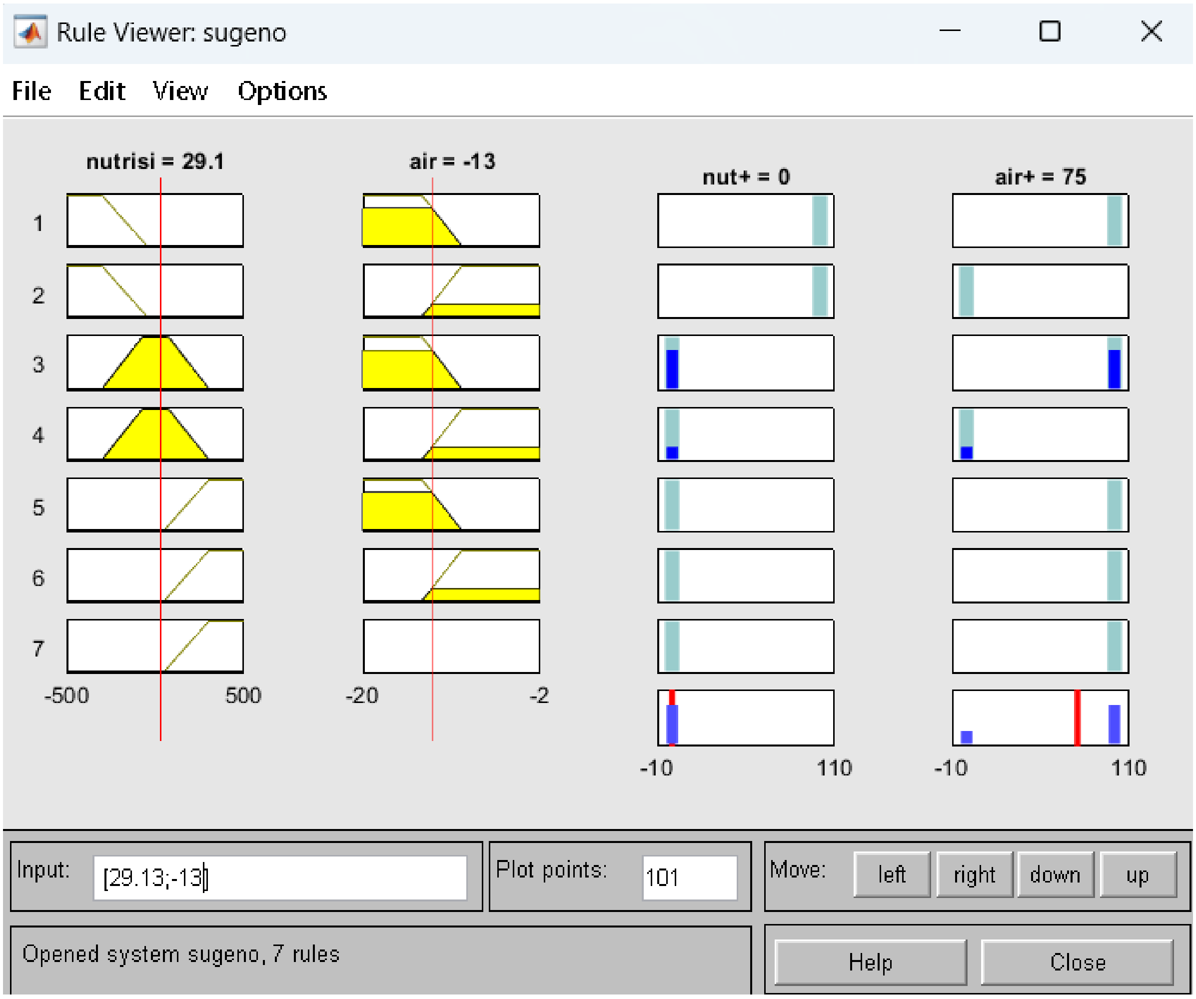


Figure 6. An Example of Fuzzy Logic Testing Result Using MATLAB

reflected promptly in the application. This monitoring capability supports user awareness, simplifies remote supervision, and reduces the need for direct manual inspection, which is particularly beneficial for rural or off-site farming operations. The application interface also supported user friendly operation, enabling easier decision making based on actual environmental conditions.

5) Control System Performance

Figure 7 shows the smart nutrient control system performance. The nutrient level gradually increased and reached a peak of 794 ppm, indicating zero overshoot. Within approximately 14 minutes, the system stabilized the nutrient level at 760–840 ppm, achieving a settling time of 840 seconds.

6) System Stability and Adaptiveness

Figures 8 and 9 show the results of the system stability and adaptability test. The first test started with a nutrient concentration of 628 ppm. The system detected the decrease and activated the nutrient valve. In Figure 8, the nutrient level gradually increased and stabilized around 800 ppm after approximately

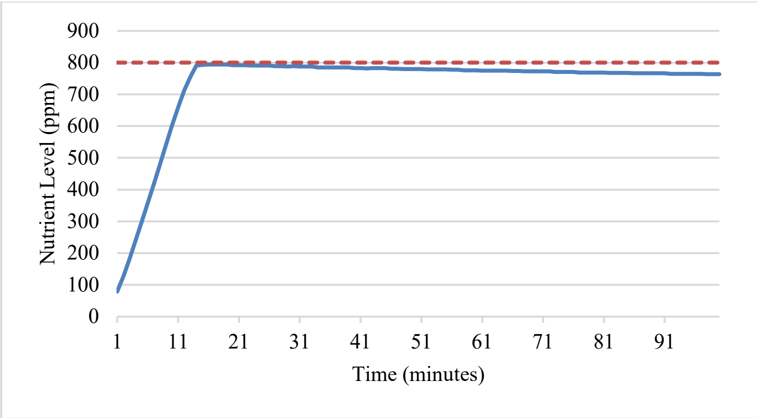


Figure 7. Smart Nutrient Control System Performance

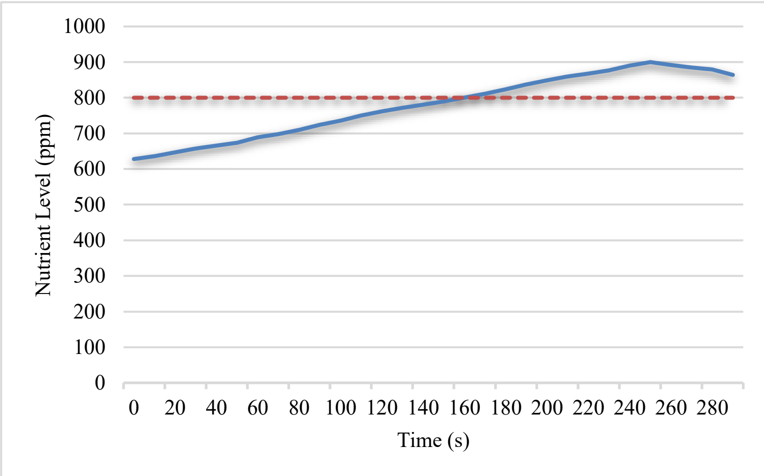


Figure 8. System Response to Sudden Decrease in Nutrient Level

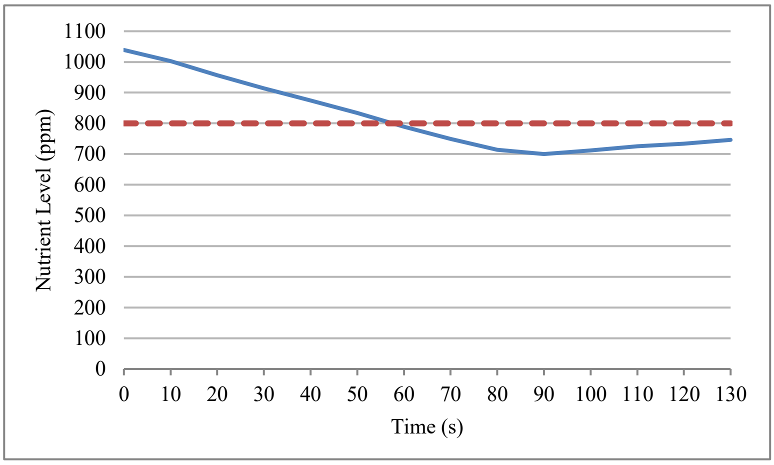


Figure 9. System Response to Sudden Increase in Nutrient Level

160 seconds, with an overshot of 12.5%. The second test started with a nutrient level at 1039 ppm. This sudden spike was detected by the sensors, and the nutrient error was calculated as +239 ppm, indicating a nutrient concentration significantly above the setpoint. In response, the fuzzy logic controller did not activate the nutrient valve but instead activated the water valve to dilute the solution. After the water valve was activated for 60 seconds, the TDS level gradually decreased and stabilized near the target value of 800 ppm.

7) Plant Growth Metrics

Table 12 shows the growth of celery plants in the fuzzy logic-controlled system, while Table 13 shows growth data for manually controlled hydroponics. In Table 12, celery plants exhibited an average 7.7

TABLE 12
CELERY PLANT GROWTH WITH FUZZY LOGIC NUTRITION CONTROL AND IOT SYSTEM

Days	Average Plant Height (cm)	Average Stem Diameter (cm)	Average Leaf Width (cm)	Leaf Color
1	12.30	0.40	1.70	Bright green
2	13.00	0.46	1.90	Bright green
3	13.90	0.48	2.00	Dark green
4	14.60	0.50	2.20	Bright green
5	15.30	0.54	2.40	Bright green
6	16.10	0.58	2.50	Bright green
7	17.00	0.60	2.60	Dark green
8	18.30	0.64	2.90	Bright green
9	19.10	0.69	3.20	Bright green
10	20.00	0.70	3.40	Bright green

TABLE 13
CELERY PLANT GROWTH WITHOUT FUZZY LOGIC NUTRITION CONTROL AND IOT SYSTEM

Days	Average Plant Height (cm)	Average Stem Diameter (cm)	Average Leaf Width (cm)	Leaf Color
1	12.30	0.40	1.80	Bright green
2	12.90	0.43	2.20	Pale green
3	13.30	0.43	2.30	Pale green
4	13.80	0.46	2.30	Dark green
5	14.60	0.46	2.40	Dark green
6	15.10	0.47	2.50	Dark green
7	15.30	0.48	2.50	Bright green
8	15.60	0.48	2.50	Bright green
9	15.70	0.48	2.60	Pale green
10	16.10	0.48	2.60	Bright green

TABLE 14
COMPARISON OF THE RESULTS OF THIS RESEARCH WITH OTHER RESEARCH

Parameter	(This Research)	Nurmahaludin	Suryatini
IoT-Based Nutrient Setting	Yes	No	Yes
IoT-Based Monitoring	Yes	No	Yes
Fuzzy type	Sugeno	Sugeno	Mamdani
Initial TDS (ppm)	79	400	1007
Setpoint (ppm)	800	600	1225
Time Interval	100 minutes (data per minute)	270 seconds (data per 10 seconds)	300 seconds (data per second)
Maximum Output (ppm)	794	618.72	1,923
Overshoot (%)	0%	3.12%	57%
Settling Time (±5%)	840 seconds (14 minutes)	138 seconds	50 seconds

cm increase in height, an average 0.3 cm increase in stem diameter, and an average 1.7 cm increase in leaf width, with consistently bright green leaf color. In contrast, Table 13 shows an average height increase of only 3.8 cm, an average stem diameter increase of 0.08 cm, and an average leaf width increase of 0.8 cm, with some leaf discoloration due to nutrient deficiencies.

Figure 10 presents a visual comparison of average plant height, average stem diameter, and average leaf width. Celery plants under fuzzy logic control experienced more consistent daily growth in height (0.7 cm - 1.3 cm, averaging 0.86 cm) compared to those without fuzzy control (0.1 cm - 0.8 cm, averaging 0.42 cm). Stem diameter growth followed a similar trend, with fuzzy logic-controlled plants showing a daily increase of 0.01 cm - 0.06 cm compared to 0.00 cm - 0.03 cm in manually controlled plants. Leaf width also grew more under fuzzy logic control (0.19 cm daily) compared to manual control (0.09 cm daily).

B. Discussion of Novelty and Contribution

A comparison of the results of this study with [24] and [21] is shown in Table 14. A comparative analysis was conducted focusing on key parameters of hydroponic nutrient control systems using fuzzy logic and IoT. Both this study and [24] implemented the Sugeno fuzzy type, known for its computational efficiency, whereas [21] used the Mamdani model, which offers more descriptive reasoning but often slower performance. All three studies use errors in the membership function as input, but the range of each membership function used varies.

From an initial condition perspective, this study started with the lowest TDS level (79 ppm), making it the most challenging scenario, while [24] and [21] began from 400 ppm and 1007 ppm, respectively. In terms of control performance, this study achieved the best precision with 0% overshoot, ensuring no risk of nutrient overdose. Nurmahaludin et al. [24] reported a minor overshoot of 3.12%, which is still within an acceptable range, while [21] experienced a high 57% overshoot, which may endanger plant health due to excessive nutrient concentration. The use of Sugeno type fuzzy logic contributes to reduced overshoot compared to Mamdani, because its crisp numerical output enables more precise and stable control actions. In contrast, Mamdani's reliance on fuzzy output sets and centroid defuzzification often results in less predictable responses and higher overshoot, especially in systems requiring fine-tuned control such as nutrient dosing.

Regarding settling time, [21] stabilized the fastest at 50 seconds, followed by [24] with 138 seconds. However, this study, while having a longer settling time of 840 seconds (14 minutes), demonstrated the most stable behavior with no overshoot, making it suitable for sensitive hydroponic environments that prioritize long term plant safety over rapid correction. This longer settling time is due to the smoother and more controlled output produced by the Sugeno method, which avoids sudden control actions and results in a slower but more stable response.

Similar to other studies [21], [22], [26], IoT can be used to monitor several important parameters in hydroponic systems, such as nutrient levels, water levels, and temperatures in hydroponic systems. However, only this study and [21] supported both remote nutrient setting and real time monitoring. Research done by Nurmahaludin [24] did not incorporate IoT, limiting flexibility and scalability. The system in [21] uses only fixed setpoint values from the database or slider, without considering changes in nutritional requirements based on the age or growth phase of the plant (germination, vegetative, generative, etc.). A distinctive feature of this study is the dynamic adjustment of nutrient concentration based on the plant's age, which is predefined in the IoT application. This enables the system to gradually increase nutrient levels by the crop's growth stage, ensuring optimal nutrient delivery and minimizing the risk of overfeeding at early stages.

The results in Figures 8 and 9 demonstrate the system's ability to adapt and maintain stability in response to dynamic nutrient fluctuations. In the first scenario, where the nutrient concentration was initially low at 628 ppm, the system responded appropriately by activating the nutrient valve. Although an overshoot of 12.5% occurred, the nutrient level stabilized around the 800 ppm setpoint within 160 seconds, indicating that the controller can handle nutrient deficiencies effectively. In the second scenario, where the system faced a sudden excess of nutrients at 1039 ppm, the fuzzy logic controller accurately identified the over concentration and responded by activating only the water valve. The solution was diluted over 60 seconds, successfully reducing the nutrient level to within an acceptable range around the setpoint. These results confirm that the system can correct both nutrient deficiencies and excesses through different control strategies, supporting the adaptability and robustness of the Sugeno fuzzy logic controller in maintaining stable hydroponic conditions. The results of this study differ from those of [26], which showed excessive nutrient levels for more than three days. This condition can harm the growth of hydroponic plants.

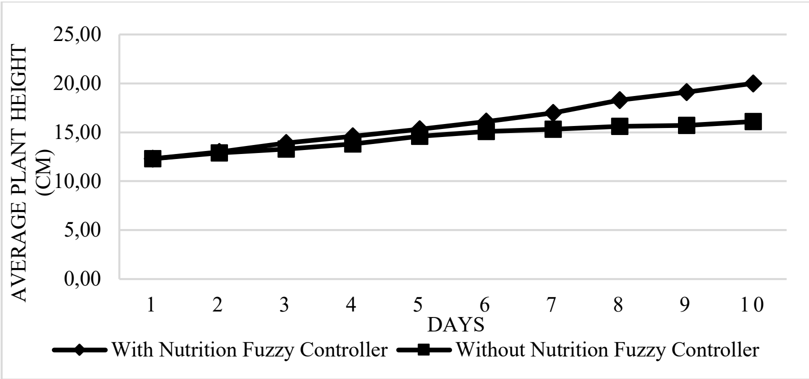
The growth data in Tables 12 and 13, as well as the visual comparison in Figure 10, indicate that celery plants grown under the fuzzy logic-controlled system experienced significantly better growth than those under manual control. Average plant height increased by 102.6%. Average stem diameter increased by 275%, while average leaf width increased by approximately 112.5%. Consistent with other researchers' findings, these substantial improvements across all growth parameters demonstrate the effectiveness of the fuzzy logic controller in maintaining optimal nutrient conditions, which leads to healthier and more vigorous plant development [21], [31].

C. Limitation

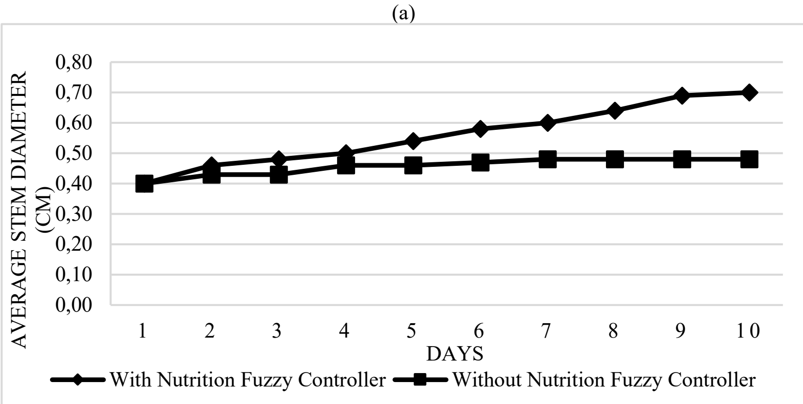
Although the proposed system showed effective nutrient regulation and improved plant growth, several limitations must be noted. The system currently does not incorporate other important factors such as pH or light intensity, which also affect hydroponic performance. In addition, the testing was limited to celery plants and conducted on a small scale, so further validation is required for different crops and larger systems. The fuzzy rules were manually defined and could benefit from adaptive optimization in future work.

D. Implications of Findings

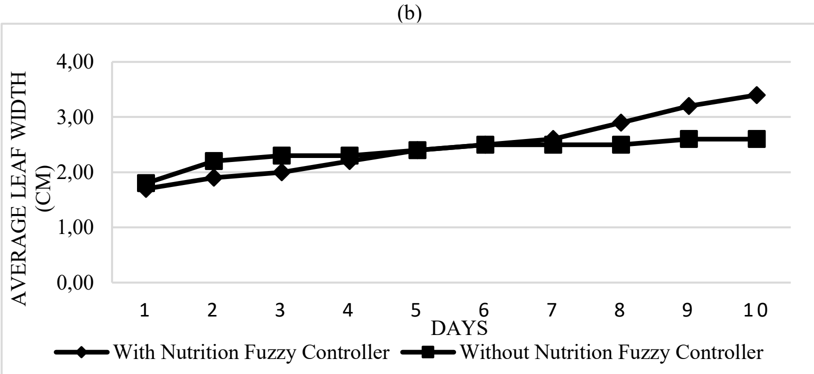
The findings of this study have meaningful implications for both practical implementation and future



(a)



(b)



(c)

Figure 10. Comparison of Celery Plant Growth in Hydroponics Controlled by Fuzzy Logic and Without Fuzzy Logic on (a) Average Plant Height, (b) Average Stem Diameter, and (c) Average Leaf Width

research. Practically, integrating a Sugeno-type fuzzy logic controller with IoT enables automated and adaptive nutrient regulation based on plant growth stages, which is especially beneficial for small-scale or rural farmers with limited technical capacity. Real time monitoring via a mobile application enhances usability, enabling users to make timely decisions without physically accessing the system. The system's ability to correct both nutrient deficiency and excess contributes to more precise and sustainable hydroponic practices. Theoretically, this study offers a foundation for the development of more advanced fuzzy-based control systems, such as those incorporating additional variables (e.g., pH, light intensity) or adaptive rule tuning through AI. Moreover, the approach can be scaled and adapted to other crops with varying nutrient needs, thus broadening its potential impact on precision agriculture.

IV. CONCLUSION

This study successfully developed a smart hydroponic nutrient control system combining Sugeno-type fuzzy logic and IoT monitoring. The fuzzy controller adaptively regulates nutrient and water levels based on plant growth stages, effectively correcting both deficiencies and excesses. The system achieved stable control performance with zero overshoot and responsive adaptation to environmental disturbances. Real time monitoring through a smartphone application enables users to track system status remotely, enhancing practicality and usability. Experimental results on celery plants show significant improvements in growth metrics compared to manual control, confirming the system's effectiveness in promoting healthy plant development. Future work may include integrating additional variables such as pH and light intensity, expanding crop types, and applying adaptive fuzzy rule tuning to further enhance control accuracy and scalability.

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REFERENCES

[1] Tranggono, R. M. J. I. Akbar, V. Z. R. Putri, N. A. Arifah, O. G. Wikarsa, and R. J. Ramadhan, 'Krisis Ketahanan Pangan Penyebab Ketergantungan Impor Tanaman Pangan di Indonesia', *AZZAHRA: Scientific Journal of Social and Humanities*, vol. 1, no. 2, Art. no. 2, May 2023.

[2] F. Luthfikahana *et al.*, 'Upaya Pemanfaatan Lahan dengan Metode Hidroponik sebagai Upaya Pemenuhan Kebutuhan Masyarakat Desa Tumbal Kecamatan Comal', *Kampelmas*, vol. 2, no. 2, pp. 1595–1608, Oct. 2023.

[3] S. Isnaeni and A. M. Ramadhan, 'Penggunaan Vertikultur Teras Bangku untuk Pengembangan Budidaya Sayuran di KWT Mawar Bodas, Tasikmalaya', *Jurnal Abdimas Kartika Wijayakusuma*, vol. 2, no. 1, Art. no. 1, Sep. 2021, doi: 10.26874/jakw.v2i1.92.

[4] M. Siregar, *Budidaya Seledri secara Akuaponik*. Sukoharjo: Penerbit Tahta Media, 2023.

[5] D. Abd-Elkader and A. Alkharpotly, 'Effect of Nitrogenous Concentration Solutions on Vegetative Growth, Yield And Chemical Characters of Celery (Apium Graveolens L.)', *Journal of Plant Production*, vol. 7, no. 11, pp. 1201–1206, Nov. 2016, doi: 10.21608/jpp.2016.46970.

[6] H. Kumar and D. A. Agarwal, 'Comparative Study of Celery (Apium Graveolens) on Growth, Yield and Quality under Different Growing Conditions', *The Indian Journal of Agricultural Sciences*, vol. 94, no. 7, Art. no. 7, Jul. 2024, doi: 10.56093/ijas.v94i7.140506.

[7] M. Sakamoto, Y. Komatsu, and T. Suzuki, 'Nutrient Deficiency Affects the Growth and Nitrate Concentration of Hydroponic Radish', *Horticulturae*, vol. 7, no. 12, Art. no. 12, Dec. 2021, doi: 10.3390/horticulturae7120525.

[8] E. Solis-Toapanta, P. R. Fisher, and C. Gómez, 'Effects of Nutrient Solution Management and Environment on Tomato in Small-scale Hydroponics', *HortTechnology*, vol. 30, no. 6, pp. 697–705, Dec. 2020, doi: 10.21273/HORTTECH04685-20.

[9] E. K. Pramartaningthyas, S. Ma'shumah, and M. I. Faud, 'Analisis Performa Sistem Kendali pH dan TDS Terlarut Berbasis Internet of Things pada Sistem Hidroponik DFT', *Jurnal RESISTOR (Rekayasa Sistem Komputer)*, vol. 5, no. 1, Art. no. 1, Apr. 2022, doi: 10.31598/jurnalresistor.v5i1.954.

[10] L. A. Kurniawan and A. Amirullah, 'Monitoring and Controlling of pH Levels and Plant Nutrition Supplied by Standalone Photovoltaic in a Greenhouse Hydroponic System using Arduino Uno', *ELKHA : Jurnal Teknik Elektro*, vol. 13, no. 1, Art. no. 1, Apr. 2021, doi: 10.26418/elkha.v13i1.45657.

[11] S. L. Ching, T. F. Siang, A. Chai, and C. P. Ching, 'Design and Develop an IoT Automated Nutrient Control in a Hydroponic System', *Future Sustainability*, vol. 3, no. 3, Art. no. 3, Aug. 2025.

[12] J. E. Suseno, M. F. Munandar, and A. S. Priyono, 'The Control System for The Nutrition Concentration of Hydroponic using Web Server', *J. Phys.: Conf. Ser.*, vol. 1524, no. 1, p. 012068, Apr. 2020, doi: 10.1088/1742-6596/1524/1/012068.

[13] S. F. Mujiyanti, S. N. Patrialova, M. F. Febrian, and M. Kartika, 'Design and Implementation of Nutrition Control System for Optimization of Hydroponic Plant Growth', in *2021 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*, Dec. 2021, pp. 52–57. doi: 10.1109/ICAMIMIA54022.2021.9807772.

[14] M. W. Hamdani, 'Perancangan dan Implementasi Metode Kontrol Fuzzy Logic Mamdani pada Sistem Kontrol TDS dan pH Hidroponik', *JTT (Jurnal Teknologi Terpadu)*, vol. 10, no. 2, pp. 171–183, Oct. 2022, doi: 10.32487/jtt.v10i2.1555.

[15] A. Malik and R. Hartono, 'Sistem Otomatis Pembuatan Nutrisi Ideal untuk Tanaman Pakcoy Menggunakan kendali Logika Fuzzy', *Jurnal Ilmiah Telekomunikasi, Kendali dan Elektronika Terapan*, vol. 9, no. 2, Art. no. 2, Oct. 2021, doi: 10.34010/telekontran.v9i2.5624.

[16] M. N. T. Perera *et al.*, 'Intelligent Algorithm for Optimizing Hydroponic Solution in IoT-Integrated Agriculture Systems', in *2024 Moratuwa Engineering Research Conference (MERCon)*, Aug. 2024, pp. 133–138. doi: 10.1109/MERCon63886.2024.10689134.

[17] I. Agustian, B. I. Prayoga, H. Santosa, N. Daratha, and R. Faurina, 'NFT Hydroponic Control Using Mamdani Fuzzy Inference System', *Journal of Robotics and Control*, vol. 3, no. 3, pp. 374–385, May 2022, doi: 10.18196/jrc.v3i3.14714.

[18] Waluyo, A. Widura, F. Hadiatna, and D. Anugerah, 'Fuzzy-Based Smart Farming and Consumed Energy Comparison Using the Internet of Things', *IEEE Access*, vol. 11, pp. 69241–69251, 2023, doi: 10.1109/ACCESS.2023.3291616.

[19] P. Atmaja and N. Surantha, 'Smart Hydroponic Based on Nutrient Film Technique and Multistep Fuzzy Logic', *IJECE*, vol. 12, no. 3, p. 3146, Jun. 2022, doi: 10.11591/ijece.v12i3.pp3146-3157.

[20] M. C. Untoro and F. R. Hidayah, 'IoT-Based Hydroponic Plant Monitoring and Control System to Maintain Plant Fertility', *Intek*, vol. 9, no. 1, pp. 33–41, Apr. 2022, doi: 10.31963/intek.v9i1.3407.

[21] F. Suryatini, S. Pancono, S. B. Bhaskoro, and P. M. S. Muljono, 'Sistem Kendali Nutrisi Hidroponik berbasis Fuzzy Logic berdasarkan Objek Tanam', *ELKOMIKA*, vol. 9, no. 2, p. 263, Apr. 2021, doi: 10.26760/elkomika.v9i2.263.

[22] A. B. Primawan and N. D. L. Kusuma, 'Nutrition Control in Nutrient Film Technique Hydroponic System Using Fuzzy Method', *E3S Web Conf.*, vol. 475, p. 04002, 2024, doi: 10.1051/e3sconf/202447504002.

[23] E. Maya Olalla, A. Lopez Flores, M. Zambrano, M. Domínguez Limaico, H. Diaz Iza, and C. Vasquez Ayala, 'Fuzzy Control Application to an Irrigation System of Hydroponic Crops under Greenhouse: Case Cultivation of Strawberries (Fragaria Vesca)', *Sensors*, vol. 23, no. 8, Art. no. 8, Jan. 2023, doi: 10.3390/s23084088.

[24] Nurmahaludin, G. R. Cahyono, and J. Riadi, 'Nutrient Concentration Control System in Hydroponic Plants Based on Fuzzy Logic', in *2020 International Conference on Applied Science and Technology (iCAST)*, Oct. 2020, pp. 141–146. doi: 10.1109/iCAST51016.2020.9557617.

[25] I. S. Nasution *et al.*, 'Embedded Fuzzy Logic for Controlling pH and Nutrition in Hydroponic Cultivation', *IOP Conf. Ser.: Earth Environ. Sci.*, vol. 1183, no. 1, p. 012113, May 2023, doi: 10.1088/1755-1315/1183/1/012113.

[26] S. Mashumah and E. Kumala Pramartaningthyas, 'Sistem Monitoring Tanaman Pakcoy Hidroponik Nutrient Film Technique (NFT) Berbasis Internet of Things', *Multitek Indonesia*, vol. 16, no. 1, pp. 47–60, Aug. 2022, doi: 10.24269/mtkind.v16i1.4342.

[27] T. Sangeetha and E. Periyathambi, 'Automatic nutrient estimator: distributing nutrient solution in hydroponic plants based on plant growth', *PeerJ Comput. Sci.*, vol. 10, p. e1871, Feb. 2024, doi: 10.7717/peerj-cs.1871.
[28] F. L. Toruan and M. Galina, 'Internet of Things- Based Automatic Feeder and Monitoring of Water Temperature, PH, and Salinity for Litopenaeus Vannamei Shrimp', *Jurnal ELTIKOM : Jurnal Teknik Elektro, Teknologi Informasi dan Komputer*, vol. 7, no. 1, pp. 9–20, Jun. 2023, doi: 10.31961/eltikom.v7i1.658.
[29] P. Prasetyawan, S. Samsugi, and R. Prabowo, 'Internet of Thing Menggunakan Firebase dan Nodemcu untuk Helm Pintar', *Jurnal ELTIKOM : Jurnal Teknik Elektro, Teknologi Informasi dan Komputer*, vol. 5, no. 1, pp. 32–39, 2021, doi: 10.31961/eltikom.v5i1.239.
[30] D. Lestari, Armaini, and Gusmawartati, 'Effects of Nutrition and Multiple Media Concentration on Growth and Yield Planting Plant Celery (Apium graveolens L.) with the Hydroponics Wick System', *Jurnal Hortikultura Indonesia (JHI)*, vol. 11, no. 3, Art. no. 3, Dec. 2020, doi: 10.29244/jhi.11.3.183-191.
[31] F. D. Zakaria, G. Priyandoko, and M. Mukhsim, 'Rancang Bangun Sistem Kontrol Untuk Pencampur Nutrisi Hidroponik Metode Pengairan DFT Berbasis Logika Fuzzy', *JTE*, vol. 13, no. 3, pp. 171–182, Sep. 2022, doi: 10.22441/jte.2022.v13i3.008.